Enhancing EPHT with Satellite-Driven PM_{2.5} Exposure Modeling and Epidemiology – Year 2 Report



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Project Team

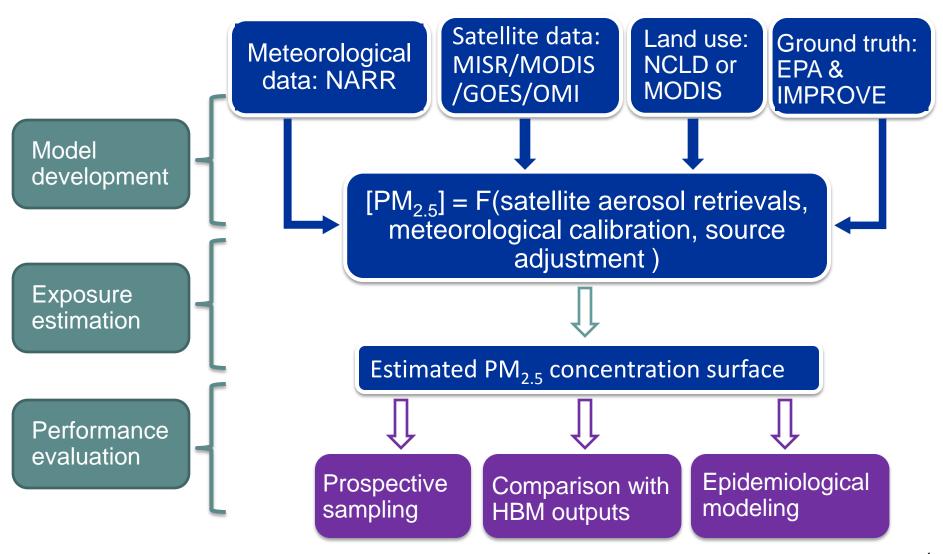
- □ Emory/RSPH: Yang Liu (PI), Jeremy Sarnat, Mitch Klein, Xuefei Hu, Heather Strosnider, and Erika Rees
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- CDC/NCEH: Judy Qualters, Paul Garbe, Helen Flowers, and Ambarish Vaidyanathan

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Research Objectives

- Extend the spatial coverage of the PM_{2.5} indicators in Tracking Network with satellite data
- Provide timely estimates of county average
 PM_{2.5} health indicators
- Evaluate satellite PM_{2.5} estimates as a alternative exposure data source in environmental epidemiologic studies and using independent ground sampling

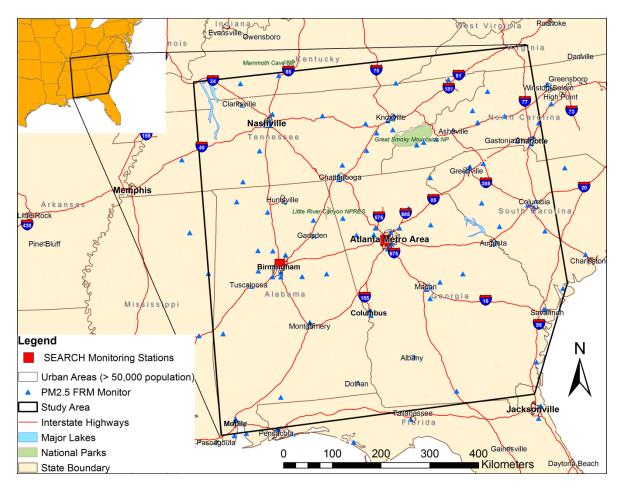
Technical Approach



Year 2 Progress Summary

- Proposed Tasks:
 - Spatial model development and comparison of NARR and NLDAS (Emory, manuscript submitted)
 - Initiation of prospective sampling (Emory)
 - 3. AOD calibration with AERONET (Emory, MSFC)
 - Nearest neighbor approach development (MSFC)
- Ahead of Schedule:
 - 5. Initiation of epidemiological analysis (Emory)
- Need More Work
 - 6. Comparison with HBM

Study Domain



- Number of monitoring sites: 119
- Exposure modeling domain: 700 x 700 km²
- SEARCH sites: 2 independent validation sites

Geographically Weighted Regression Model

GWR allows model parameters to vary in space to better capture spatially varying AOD-PM relationship – major advantage over global regression models.

Model Structure

$$\begin{aligned} [PM_{2.5}]_{(x,y)} &\sim \beta_{0(x,y)} + \beta_{1(x,y)} \times AOD + \beta_{2(x,y)} \times PBL + \beta_{3(x,y)} \times RH \\ &+ \beta_{4(x,y)} \times Temp + \beta_{5(x,y)} \times Wind_Speed + \beta_{6(x,y)} \times Forest_Cov \ er \end{aligned}$$

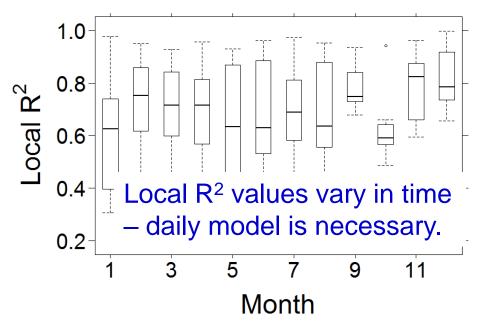
Datasets (2003):

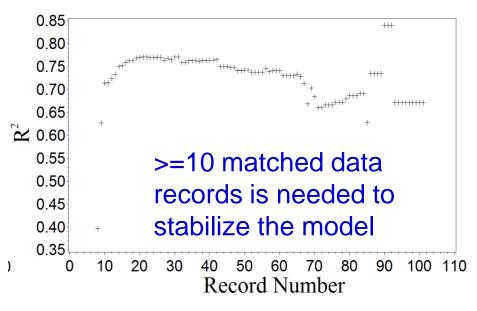
PM_{2.5} – EPA / IMPROVE daily measurements AOD – MODIS collection 5 (10 km) or GASP (4 km) Meteorology – NLDAS-2 (14 km) or NARR (32 km) Land use: NLCD 2001

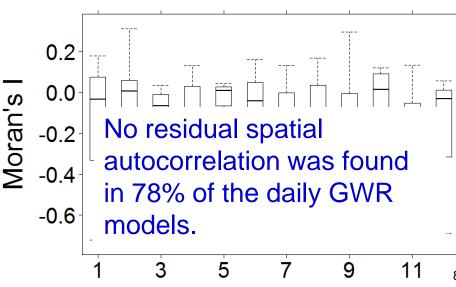
Model is fitted at daily level

Model Fitting Results

Max Obs. Per Day	101
Model Days	137 (37.5%)
Total Obs.	4,477







Month

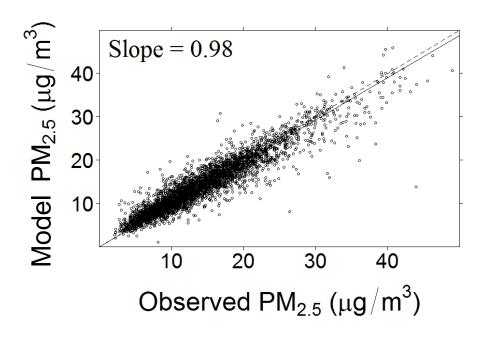
Model Performance Evaluation

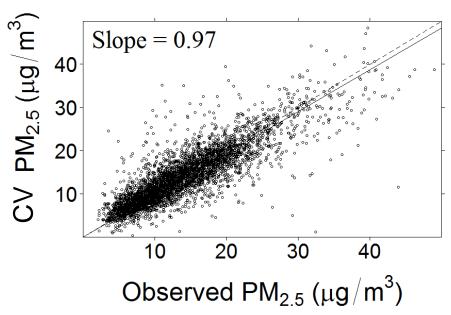
	Mean	Min	Max
Model R ²	0.86	0.56	0.92
CV R ²	0.70	0.22	0.85

SEARCH site predictions

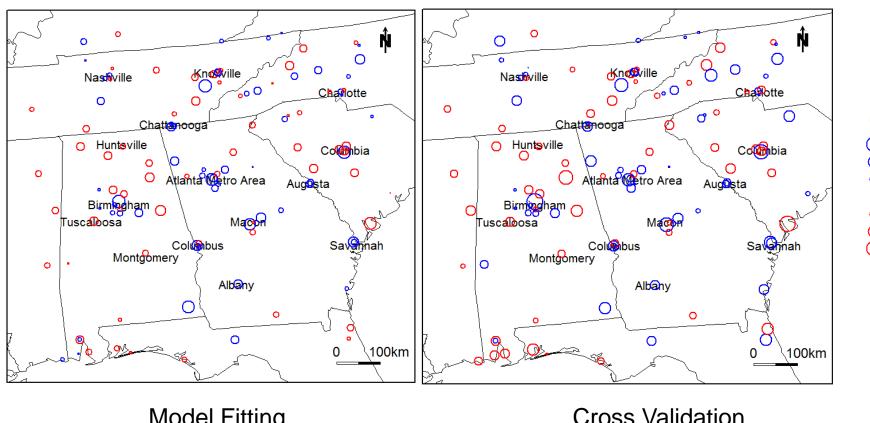
Site	N	Annual PM _{2.5}	r
ВНМ	85	19.1 μg/m³	0.90
JST	87	15.3 μg/m³	0.82

Putting all the data points together, we see unbiased estimates





Spatial Pattern of Model Bias



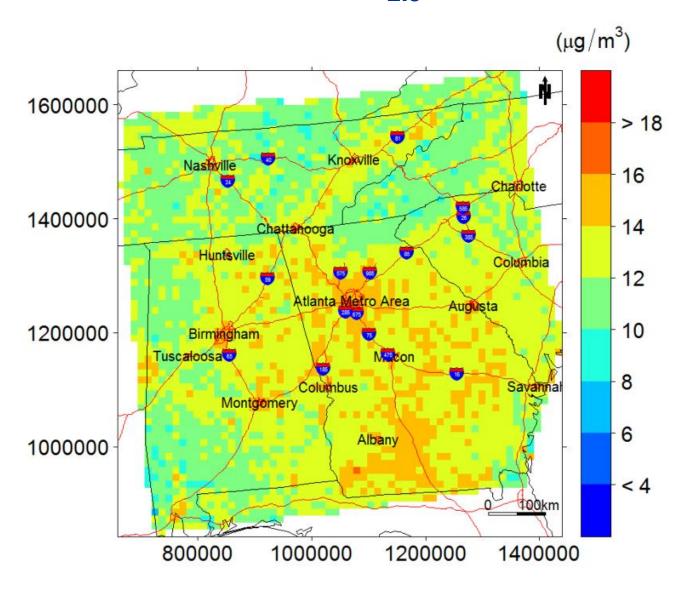
 $(\mu g/m^3)$

Model Fitting

Cross Validation

Negative and positive model / CV residuals are randomly distributed.

Model Predicted Mean PM_{2.5} Surface



Note: annual mean calculated with 137 days

Comparison with Other Models

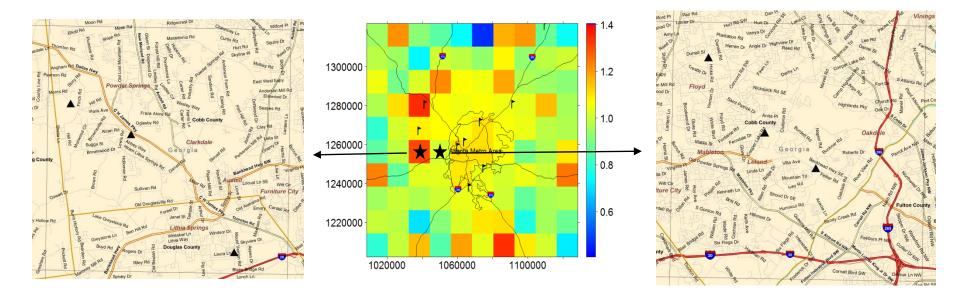
□ Pros:

- Better performance than global regression models
- Better reflection of temporal variability than LUR models
- Stronger physical base than kriging models
- Simpler and faster than air quality models

Cons:

- Integration with air quality models?
- Statistical data filling is under study
- Higher resolution data will become available soon

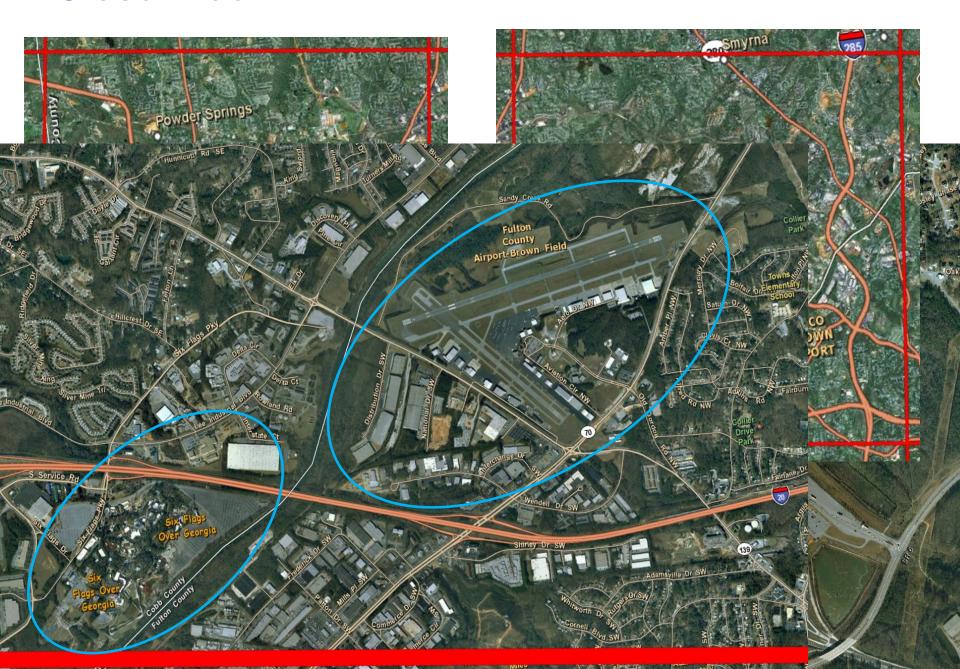
Strategy



- □ Identify a "hot" and a "cool" pixel based on ratios of GWR daily PM_{2.5} concentrations over regional mean.
- 3 sampling locations > 3 km apart in each 12 km pixel
- ~20 24-hr samples in the next 6-9 months

So far, 3 sites located, portable samplers tested, made 2 sampling trips.

A Closer Look



Rational and Approach

For satellite data to be considered a reliable source of exposure estimates in health studies, both the spatial pattern and absolute levels of predicted $PM_{2.5}$ concentrations are important.

General calibration model structure (fitted annually)

$$AERONET AOD = \alpha + \beta_1 \times satellite AOD + season$$
$$+ \beta_2 \times satellite AOD \times season$$

Caveat: without calibration, MODIS can't be used for seasonal trend analysis, GOES can't be used for either seasonal or interannual trend analysis

Rational and Approach

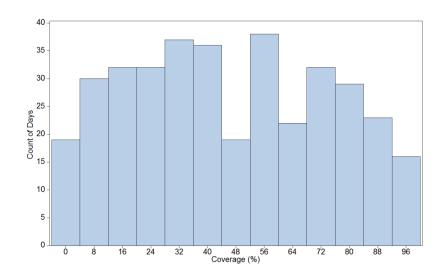
Problem: cloud cover causes a lot of data missingness. Without any treatment, best possible coverage is ~ 50%.

Hypothesis: missing AOD values due to small clouds can be filled with its nearest neighbors without significantly disturbing the predicted $PM_{2.5}$ surface.

Method: maximum distance over which nearby observations may be used to fill in missing grid cell values = 20 km

4. Nearest Neighbor Filling

Preliminary Results



Raw MODIS, 2007

60 -														
50 -														
40 -														
Count of Days														
20 -														
10 -														
0	4	12	20	28	36	44 Co	52 verage (60	68	76	84	92	100]
						00	relage (,,,,						

NN filled MODIS, 2007

Coverage (%)	N_days	Mean
Raw	365	46.04
NN	365	65.53

	RMSE (μg/m³)	Relative Accuracy (%)
Raw_NARR	5.61	60.4
NN_NARR	4.82	66.8

NN filling: (1) improve coverage (2) improve model performance

Plan of epidemiological analysis

- 1. Communicate with epidemiologists on data format, structure, and modeling needs
- Generate daily PM_{2.5} estimates using calibrated, nearest neighbor-filled MODIS AOD for 2000 – 2007
- 3. Spatially join with zip code level patient addresses
- 4. Work with epidemiologists to develop spacetime model
- 5. Evaluate resulted exposure-response functions

Year 3 Tasks

- Emory
 - MODIS/GOES data fusion
 - Final GWR PM_{2.5} modeling
 - Development of new model structure
 - Field sampling and sample analysis
 - Health effects modeling and evaluation
- MSFC
 - Further study of gap filling techniques
 - Finalization of gridded aerosol data
- CDC
 - Comparison between HBM and satellite
 - Project benefit assessment